AI-Augmented Scenario-Based Learning: An Exploratory Study of Human–AI Collaboration Modes in Engineering Education

Dr. Chenxi Yuan, Southern Illinois University Edwardsville

Chenxi Yuan is an associate professor in the Department of Construction, School of Engineering, Southern Illinois University Edwardsville. He manages the Transparent Civil Infrastructure System Lab (T-CIS), which integrates sensing, informatics, visualization, and artificial intelligence to support the measurement, interpretation, and decision-making processes associated with construction objects, underground utilities, and the above-ground built environment. His recent research and teaching focus on human–AI collaborative workflows, exploring how artificial intelligence can augment human judgment in construction inspection, digital modeling, and data-driven project decision-making. He adopts a teacher-scholar model by directly incorporating his research outcomes into classroom instruction, preparing students with up-to-date construction technologies, analytical tools, and management skills. Chenxi obtained his bachelor of Mechanics Engineering from Central South University, China in 2007 and his Master of Civil Engineering from Tongji University, China in 2010. After graduation, he worked at ARUP consultant company as an assistant engineer for two years. Then he continued his PhD study and obtained his doctorate in Civil Engineering at Purdue University in 2018. In Summer 2022, he received a faculty residency fellowship and worked for McCarthy Construction Company's Virtual Design and Construction group to enhance his classroom skills. At T-CIS Lab, our mission is to address the pressing challenges faced by civil infrastructure in teaching and research through developing, implementing and sharing the state-of-the-art solutions. We strive to create a thriving community of researchers, engineers (current and future), and visionaries who collaborate to readily provide transparent civil infrastructure system (CIS) information. Core Values: 1. Collaboration: We foster a collaborative environment that encourages cross-disciplinary partnerships, promoting knowledge exchange and accelerating the pace of discovery. 2. Social Impact: Our lab is dedicated to improving the lives of people around the world by creating infrastructure systems that promote social equity, accessibility, and community well-being. 3. Sustainability: We are committed to promoting sustainable practices throughout the life cycle of civil infrastructure. Our solutions focus on reducing environmental impact, conserving resources, and enhancing long-term viability. 4. Transparent Governance and Policy: Examining governance models and policy frameworks that promote transparency, inclusivity, and accountability in civil infrastructure planning and management.

Abhishek Khatiwada, Southern Illinois University Edwardsville

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Chenxi Yuan
Department of Construction
Southern Illinois University Edwardsville
Edwardsville, Illinois, USA

Abhishek Khatiwada
Department of Civil Engineering
Southern Illinois University Edwardsville
Edwardsville, Illinois, USA

Abstract
Preparing future construction engineers to engage critically and responsibly with artificial intelligence (AI) systems is increasingly essential as digital technologies reshape professional engineering practice. This paper presents the design and initial classroom implementation of a multimedia-based interactive platform developed using the open-source workflow automation tool n8n. The platform simulates realistic infrastructure inspection scenarios and enables structured comparison of three human–AI collaboration modes: human-only decision-making, AI-assisted (collaborative), and AI-guided (directive) interaction. Grounded in scenario-based learning and reflective instructional design, the system integrates short video clips, contextual inspection data, structured decision prompts, and guided reflection questions to immerse students in authentic, context-rich engineering tasks. The instructional objective is to help students critically evaluate AI-generated recommendations, assess decision confidence, and reflect on the appropriate allocation of authority between human judgment and algorithmic support.

The platform was deployed across multiple undergraduate construction engineering courses. Students completed comparable inspection tasks under each collaboration mode, enabling exploratory comparison of performance, confidence, and preference patterns. Descriptive results indicate meaningful differences in how students perceive and engage with AI across modes, particularly regarding autonomy and support. This paper contributes a modular implementation framework and structured instructional model for responsibly integrating AI collaboration paradigms into engineering curricula.

1. introduction

The rapid integration of artificial intelligence (AI) into engineering practice is reshaping how future professionals must be trained. AI techniques—including machine learning, computer vision, and generative models—are increasingly embedded across civil and construction workflows, from structural health monitoring and predictive maintenance to planning and infrastructure analysis [1–4]. As these tools evolve from automated assistants into collaborative decision partners, educators face new challenges: how to prepare students not only to use AI tools effectively but also to critically evaluate and collaborate with them in engineering contexts?

Recent studies have emphasized the need for human–AI co-agency in engineering workflows, suggesting that the most effective systems balance automation with human judgment rather than replacing it entirely [5, 6]. In parallel, AI foundation models—particularly large language models (LLMs) such as ChatGPT—have opened new possibilities for scenario-based, dialogic, and reflective learning in the classroom [7]. Researchers have proposed frameworks in which LLMs serve not only as information retrieval agents, but also as tutors, collaborators, or critics, depending on the instructional goal [8].

Despite the increasing adoption of AI in engineering education, significant gaps remain in understanding how these tools should be pedagogically integrated. A 2025 systematic review found that most applications of AI in engineering education focus on automated grading, tutoring bots, or adaptive content delivery—rather than the modeling of real-world decision-making under uncertainty [9]. Meanwhile, large-scale student surveys report that over 95% of students already use AI tools for academic tasks [7], yet few programs provide structured scaffolding or curricular strategies to support responsible use in domain-specific settings. Recent policy analyses also show that institutional responses to AI in higher education are still emerging, with inconsistent guidelines and minimal integration into discipline-specific learning outcomes [10].

Moreover, existing studies rarely examine how different modes of human–AI interaction affect student cognition, engagement, and skill development. While the usability and ethical implications of LLMs in civil and environmental engineering classrooms have received some attention [6], there is little evidence on how students experience AI across instructional formats that vary in autonomy, support, and control.

To address this gap, this paper presents the design and classroom deployment of a multimedia-based platform powered by ChatGPT and orchestrated through n8n, an open-source automation platform. The system delivers scenario-specific video tasks, AI prompts, and structured reflection components to simulate real-world infrastructure inspection decision-making. Three human–AI interaction modes were tested: (A) human-only, (B) AI-assisted (collaborative), and (C) AI-guided.

This paper builds upon two prior studies, each of which examined narrower facets of AI use in engineering contexts. One study explored the potential of generative AI to assist instructors across the teaching lifecycle, from course design to assessment, and proposed a reflective framework for AI–instructor collaboration grounded in construction engineering education [11].

Another study focused on evaluating the effectiveness of AI-generated prompts in simulated bridge inspection tasks on behalf of transportation agencies, where students served as proxy inspectors and interacted with ChatGPT-based assistant under varying levels of autonomy [12]. Expanding from these earlier investigations, the present study adopts a broader lens rooted in engineering education. It introduces a modular instructional system powered by ChatGPT and orchestrated through n8n, designed to explore two engineering education questions:

- How do different AI–human collaboration modes influence student task accuracy, decision confidence, and learning preference?
- What are the instructional benefits and risks of positioning LLMs as collaborative versus directive agents in engineering classrooms?

By examining the outcomes of this system across multiple undergraduate course levels, this paper contributes to the design of responsible, effective, and scalable AI-powered instructional platforms for engineering education.

2. literature review

2.1 human–AI collaboration modes in engineering and education

As artificial intelligence systems become embedded in professional engineering workflows, researchers increasingly distinguish between modes of human–AI collaboration ranging from human-only control to AI-led automation. In civil and construction engineering, prior studies have examined AI applications in design automation, structural monitoring, and construction analytics, though most focus on performance outcomes rather than collaborative cognition or shared agency [1–4]. In educational contexts, emerging frameworks position large language models (LLMs) such as ChatGPT as assistants, critics, or dialogic partners depending on instructional design [6–8]. However, few empirical studies directly compare structured collaboration modes (e.g., human-only, AI-assisted, AI-guided) within the same learning task. This gap motivates the present study's evaluation of three distinct AI–human interaction configurations in a scenario-based engineering environment.

2.2 cognitive science and active learning in engineering classrooms

Constructivist learning theory emphasizes active engagement, reflection, and self-explanation as mechanisms for deeper understanding and retention. Engineering education research consistently supports pedagogies that require students to make decisions, articulate reasoning, and iterate on feedback [5, 13]. AI systems may enhance these processes when deployed as scaffolding agents that support reasoning without replacing cognitive effort. Recent studies suggest that LLMs can generate formative feedback, counterarguments, or structured prompts that promote metacognition—provided students retain interpretive control and instructors apply appropriate guardrails [7, 8]. These findings underscore the importance of designing AI interactions that preserve learner agency.

2.3 scenario-based learning in construction education

Scenario-based learning (SBL) immerses students in realistic, constraint-driven environments requiring applied judgment. In construction education, this includes video-based simulations, inspection workflows, and case-based reasoning related to safety, planning, and ethics [6, 10]. Such approaches enhance engagement and decision-making, particularly when supported by multimodal materials. However, most construction SBL platforms lack adaptive AI feedback or structured comparison of collaboration modes. Few studies investigate how workflow automation and LLM integration can support reflection or structured comparison of AI collaboration modes. This study addresses this gap by embedding multiple interaction paradigms within scenario-based inspection tasks. Figure 1 presents the intersection of AI systems, active learning principles, and scenario-based instruction that defines the framework examined in this study.

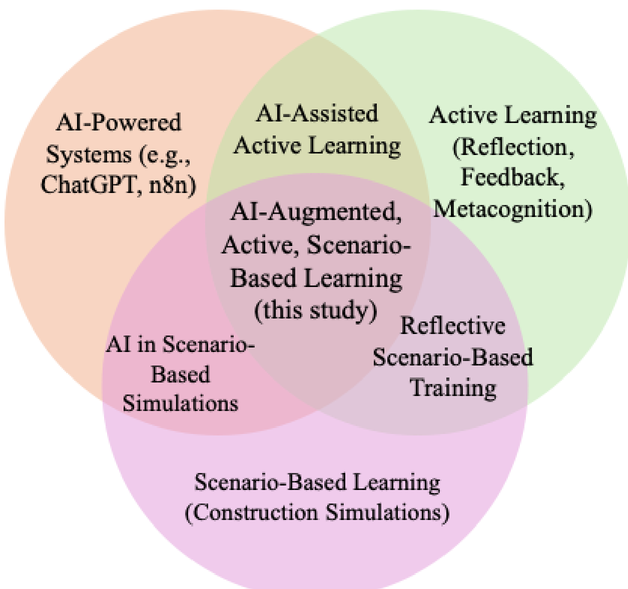

Figure 1. Integration of AI systems, active learning strategies, and scenario-based instruction

3. methodology

3.1 participants and study context

The AI-powered human–AI collaborative learning platform was deployed across three undergraduate construction engineering courses: a 100-level course (Computer Applications), a 200-level course (Construction Methods), and a 400-level course (Senior Capstone). These courses represent different stages of the undergraduate curriculum, ranging from technology-oriented skill development to applied construction decision-making and integrative project management. A total of 45 students participated in the instructional module as part of regularly scheduled coursework. Participation was embedded within normal classroom activities and did not require additional time beyond standard course expectations. Student responses were anonymized prior to analysis to protect confidentiality. The deployment served as a classroom-based instructional pilot rather than a controlled experimental study.

3.2 study design and data collection

The study employed a within-subject exploratory design to compare three structured human–AI collaboration modes: (1) human-only decision-making, (2) AI-assisted (collaborative) interaction, and (3) AI-guided interaction. Each student engaged with all three modes while analyzing the same simulated infrastructure inspection scenario. This design enabled comparison of response patterns across interaction conditions while controlling for scenario variability.

The primary research questions guiding the analysis were:

(1) How do different AI–human collaboration modes influence student task accuracy, decision confidence, and learning preference?
(2) What instructional benefits and potential risks emerge when positioning LLMs as collaborative versus directive agents in engineering classrooms?

Student responses included both structured selections and written reflections. After completing the activity, students indicated their preferred collaboration mode (human-only, AI-assisted, or AI-guided), producing closed-ended data used to summarize preference distribution. Students also provided written explanations describing their reasoning and perceptions of AI support.

Closed-ended responses were summarized using descriptive statistics. Written reflections were examined thematically to identify recurring patterns related to decision confidence, trust in AI recommendations, and perceived cognitive support. Given the exploratory nature of the classroom deployment, formal hypothesis testing was not conducted. The analysis therefore focuses on instructional observations rather than validation of a formal survey instrument.

3.3 instructional instrument

The instructional activity was delivered through a multimedia-based scenario learning platform developed using the open-source automation tool n8n and a large language model interface. The platform presented students with a simulated inspection report, embedded video clips, contextual prompts, and guided reflection questions. Rather than functioning as a traditional survey instrument, the platform operated as a guided decision interface designed to scaffold critical reasoning. Students submitted structured written responses under each collaboration mode, including justification of inspection priorities and evaluation of AI-generated recommendations.

4. system design

This section outlines the architecture and instructional logic of the AI-augmented multimedia platform developed to support reflective, scenario-driven learning in construction and civil engineering courses. The system integrates three core components: (1) a large language model interface (ChatGPT), (2) the workflow orchestration platform n8n, and (3) embedded video-based inspection tasks with structured prompts.

4.1 pedagogical framework and collaboration modes

The platform is grounded in constructivist learning theory, active learning, and human–AI collaboration paradigms. It is designed to:

- engage students in realistic inspection scenarios requiring judgment under uncertainty,
- provide configurable AI interaction modes (human-only, AI-assisted, AI-guided), and
- capture structured decision responses and reflections for instructional analysis.

This design allows instructors to vary the level of AI involvement while keeping the learning scenario constant. Across modes, students analyze a simulated bridge inspection report containing text, images, and short video walkthroughs. They interpret findings, answer scenario-specific questions, and justify their reasoning. Learning objectives—adapted across course levels—include applying domain knowledge, evaluating AI-generated recommendations, articulating structured critique, and comparing collaboration modes in terms of trust and effectiveness.

To operationalize this framework, the system implements three human–AI collaboration modes (see Table 1). The platform records which interaction mode each student uses and enables comparison of learning patterns across modes.

Table 1. Three human–AI collaboration modes

Mode	Description	Cognitive Focus
A – Human-only	Students make decisions without AI assistance	Independent reasoning and justification
B – Human-led, AI-assisted (Collaborative)	Students receive AI-generated suggestions but make final decisions	Critical engagement, comparison, and confidence calibration
C – AI-guided, Human-confirmed	AI provides full responses; students review and approve or critique	Evaluation, critique, and trust calibration

4.2 system architecture and n8n workflow

The n8n platform serves as the orchestration layer managing scenario routing, API communication with ChatGPT, response logging, and reflection capture. Through modular workflows, instructional content can be updated without modifying the underlying AI model. Figure 2 presents a conceptual overview of the workflow structure, illustrating how multimedia data, AI interaction, and reflection components are sequenced within the learning experience. Figure 3 expands this model by mapping core system functions—multimedia ingestion, prompt injection, response retrieval, and data storage—into a modular automation pipeline. The system is modular and adaptable, allowing instructors to define new scenarios or modify prompt logic without modifying core architecture.

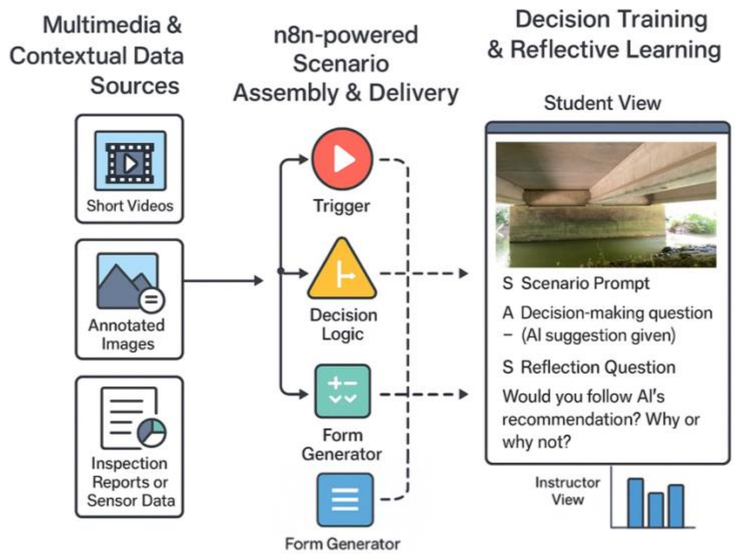

Figure 2. Using n8n to connect multimedia data for infrastructure inspection training

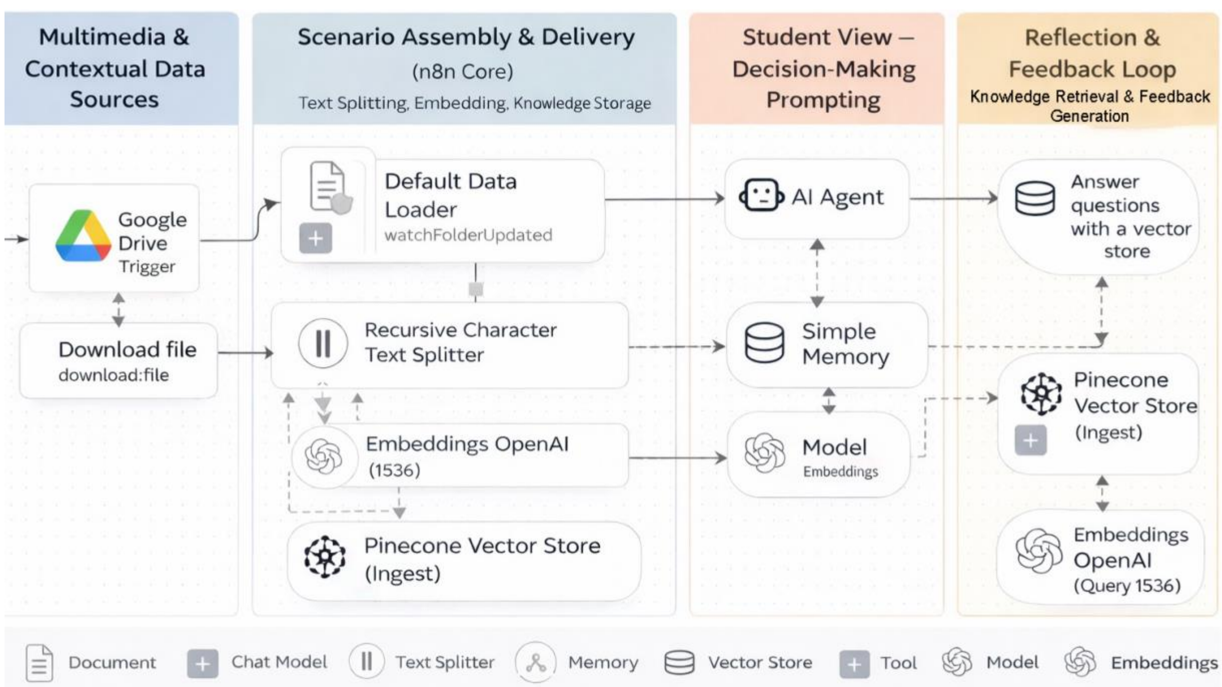

Figure 3. System-level implementation of the AI-augmented bridge inspection workflow using the n8n automation platform

To support scalability and adaptability, the system also follows modular AI engineering principles [14]. As illustrated in Figure 4, the orchestration layer (n8n) manages instructional logic and data flow, while the LLM component generates contextual language outputs. This separation enables independent updating of prompts, scenarios, and AI models without altering the pedagogical structure. By embedding human oversight and reflection within the workflow, the platform supports transparent, human-in-the-loop instructional design suitable for engineering education contexts.

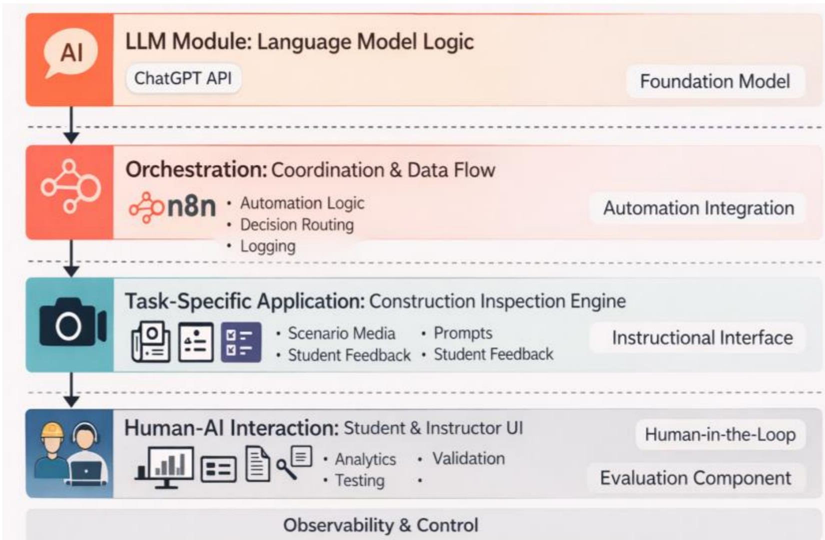

Figure 4. Mapping the interactive platform to AI engineering layers

4.3 scenario design and learning interaction

Each inspection module includes:

- A brief video walkthrough (30–90 seconds),
- A few inspection reports from Departments of Transportation in PDF style,
- Scenario-based questions (multiple-choice or short-answer), and
- A structured reflection prompt addressing confidence and AI influence

In AI-assisted and AI-guided modes, prompt templates dynamically incorporate scenario variables (e.g., bridge type, anomaly description) to generate contextualized AI suggestions.

Students interact with a streamlined interface presenting multimedia content, structured prompts, and AI outputs (when applicable). The design emphasizes clarity and reflective engagement. Instructors have access to optional analytics dashboards summarizing mode-specific performance, reflection patterns, and usage behavior, supporting formative evaluation and instructional refinement.

5. course implementation

The platform was deployed in three undergraduate construction engineering courses (100-, 200-, and 400-level) through a scenario-based instructional module. The activity required approximately 60–90 minutes, including structured reflection and guided discussion. Table 2 summarizes the differentiated learning outcomes implemented across course levels.

Table 2. Scaffolded learning outcomes by course level

Course Level	Focus	Cognitive Goals (Bloom)	Sample Learning Outcomes
100-level	Awareness & Terminology	Remember, Understand	- Define key terms (AI, automation, decision-making system) - Identify basic components of an infrastructure inspection scenario - Recognize how AI might assist in construction tasks
200-level	Conceptual Understanding &Observation	Understand, Apply	- Describe common human–AI collaboration modes - Explain when AI outputs may be appropriate or risky - Apply basic judgment in scenario-based inspection tasks
400-level	Ethical Reasoning & Decision Justification	Evaluate, Create	- Justify inspection decisions in uncertain or conflicting data environments - Develop reasoned critiques of AI-supported workflows - Reflect on the ethical implications of delegating decisions to AI in safety-critical tasks

6. ethical considerations

This study reports on the design and instructional implementation of an AI-augmented learning platform deployed within regularly scheduled undergraduate construction engineering courses. Student responses analyzed in this paper were generated as part of standard classroom activities and were collected in anonymized form for instructional evaluation purposes. Participation in the activity did not alter grading policies beyond standard course expectations.

This research has received Institutional Review Board (IRB) approval from Southern Illinois University Edwardsville (Protocol #3406, Human-AI Bridge Inspection Survey) and was determined to be exempt. The analyses reported in this paper are based on classroom-based instructional deployment and are presented in a descriptive and exploratory manner to inform pedagogical design rather than to draw generalized inferential conclusions about human subjects.

7. assessment and results

The platform used in this study was originally developed to support AI-augmented bridge inspection workflows. In the present study, it is deployed in an educational setting to explore how different human–AI collaboration modes influence student engagement, reasoning, and preferences in engineering classrooms. To assess the instructional impact, the platform was used in three construction engineering courses involving a total of 45 undergraduate students. Each student completed a simulated bridge inspection task using the same report across three interaction modes, reflecting distinct human–AI collaboration models. These results are intended to provide instructional insights rather than statistical generalization.

Given the exploratory classroom nature of this implementation and the ongoing IRB review, results are reported using descriptive statistics to summarize response patterns across collaboration modes. Specifically, we report counts and percentages for categorical outcomes (e.g., mode preference and accuracy categories) and summarize scaled ratings (e.g., confidence) using measures of central tendency and variability where applicable. The intent is to characterize instructional patterns and design implications rather than to make generalized inferential claims.

7.1 performance across collaboration modes

Each student completed the same inspection scenario under the following three interaction modes:

- Mode A – Human-only: Students received no AI support and relied solely on the raw inspection report and media.
- Mode B – AI-assisted (Collaborative): Students received AI-generated suggestions but retained full decision-making control.
- Mode C – AI-guided: The AI provided complete recommendations, and students were asked to approve or critique them.

Task performance was assessed based on the number of correct answers submitted in response to scenario-specific questions. Results showed that only 10% of students in Mode A answered all items correctly, compared with 88.9% in Mode B and 100% in Mode C. These results suggest that AI support—whether collaborative or fully automated—was associated with markedly higher task accuracy. However, the distinction between Modes B and C highlights an important trade-off. While Mode C produced perfect outputs, it may not reflect meaningful student engagement or learning.

7.2 student preferences and decision confidence

Following the task, students indicated their preferred interaction mode and provided brief written reflections about their experience. As illustrated in Figure 5, the collaborative AI-assisted mode (Mode B) was the most preferred, selected by 58.2% of participants. The AI-guided mode (Mode C) was preferred by 33.9%, while only 7.9% preferred the human-only condition (Mode A). Students cited a variety of reasons for their preferences. Those favoring Mode B emphasized the balance between receiving helpful guidance and retaining control: “The AI helped me double-check things I wasn’t confident about, but I still had to think through the problem.” Those who preferred Mode C appreciated its efficiency, but some expressed concern about over-reliance: “It gave me the right answers, but I felt like I was just approving something without understanding it.” Students in Mode A reported the most cognitive effort but also the most uncertainty, with one respondent noting: “I wasn’t sure what the right answer was, and I had nothing to compare my thinking to.”

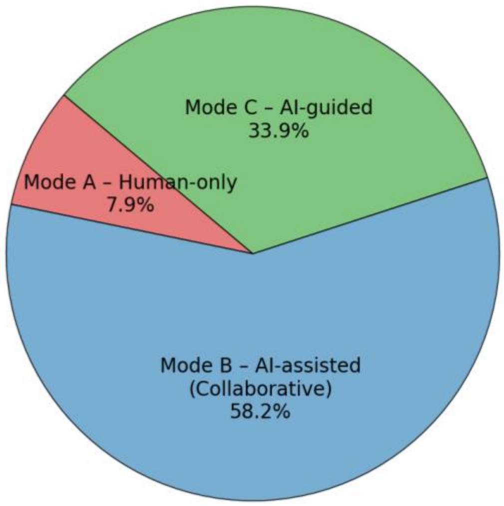

Figure 5. Student preferences for AI–human collaboration modes

Students also reported which collaboration mode left them feeling most confident in their decision making. The AI-assisted mode received the greatest confidence selection (Mode B, n = 31, 68.9%), followed by the AI-guided mode (Mode C, n = 13, 28.9%) and the human-only mode (Mode A, n = 2, 4.4%). This pattern mirrors the preference and accuracy distributions, suggesting that students most often associate collaborative AI interaction with both perceived confidence and favorable decision outcomes.

Collectively, these descriptive statistics portray a consistent pattern across preference, performance, and confidence indicators: students tended to favor and perform better with AI support that retained human agency, and they expressed lower confidence and performance when operating without AI assistance.

7.3 pedagogical implications and connection to prior research

These results support the value of AI-assisted scaffolding in engineering education. Mode B, which situates AI as a collaborative peer, not only improved student performance but was also rated highest in terms of perceived learning benefit. In contrast, the AI-guided mode may boost accuracy but at the potential cost of deeper understanding—raising important concerns about long-term skill development. The human-only condition provided an important baseline for measuring improvement and allowed insight into student reasoning without technological mediation.

These observations are consistent with prior research emphasizing the importance of human–AI co-agency in engineering contexts. Studies in both civil engineering practice and AI-assisted learning environments suggest that optimal performance often emerges when AI systems function as collaborative partners rather than fully autonomous agents [5], [6]. The strong student preference for the AI-assisted (collaborative) mode observed in this study reinforces this perspective, indicating that learners value cognitive scaffolding while retaining decision authority. The results also extend literature on large language models in engineering classrooms. Prior work has proposed that LLMs may function as tutors, critics, or dialogue partners depending on instructional design [8]. However, few studies have directly compared structured collaboration modes within the same learning task. By exposing students to human-only, AI-assisted, and AI-guided configurations within a shared scenario, this study offers comparative evidence that the pedagogical positioning of AI meaningfully shapes perceived learning value and cognitive engagement. Furthermore, the preference for AI-assisted interaction is consistent with active learning and constructivist frameworks emphasizing student agency and reflective reasoning [5], [13]. When AI guidance becomes directive, as in the AI-guided mode, task accuracy may increase, but opportunities for deeper reasoning may diminish. This supports broader concerns in engineering education literature regarding over-reliance on automated tools and the potential erosion of independent problem-solving skills. These findings suggest that the question is not whether AI should be integrated into engineering education, but how it should be pedagogically positioned.

8. discussion

8.1 lessons learned and platform scalability

Implementing the AI-augmented platform across multiple course levels provided several important insights. First, the flexibility of the n8n orchestration platform allowed for scalable deployment across diverse classroom settings without overburdening instructors. Workflows could be cloned and adapted to each assignment with minimal technical overhead, enabling seamless delivery of customized media, prompts, and AI outputs. Students initially had difficulty distinguishing between the AI-assisted (collaborative) and AI-guided (directive) experiences. This observation highlights that AI should not be presented as a single fixed tool, but rather as a flexible instructional component that can play different roles in the learning process. The platform itself represents an instructional innovation, while the classroom deployment reported here provides exploratory observations intended to inform future controlled educational studies.

8.2 contribution to instructional design theory and practice

This study contributes to emerging research on AI-in-the-loop pedagogy by empirically comparing structured human–AI collaboration modes within a shared instructional task. Rather than treating AI as a uniform instructional tool, the platform positions LLMs as configurable agents whose pedagogical role can be deliberately adjusted. By exposing students to human-only, AI-assisted, and AI-guided configurations, the system makes the allocation of authority between human judgment and algorithmic support explicit and comparable.

The findings suggest that learning outcomes are influenced not only by the presence of AI, but by how AI is positioned within the instructional workflow. Collaborative AI support appears to enhance engagement and confidence while preserving cognitive effort, whereas directive AI modes may improve efficiency at the potential expense of deeper reasoning. These distinctions provide practical guidance for instructors seeking to integrate AI tools without diminishing student agency.

8.3 implications for construction curriculum reform

The findings have direct implications for construction education reform. As the industry adopts AI-powered tools in safety management, project controls, QA/QC, and BIM workflows, students must be trained not just in technical tasks, but in evaluating algorithmic suggestions, reasoning under uncertainty, and communicating AI-supported decisions.

This platform aligns well with modern ABET and ACCE outcomes that emphasize lifelong learning, ethics, and interdisciplinary knowledge integration. By embedding reflection and judgment alongside technical accuracy, the system supports the development of future-ready professionals who are literate not only in construction methods, but in human–AI collaboration—a vital competency for digitally augmented job sites.

8.4 limitations

Several limitations should be acknowledged when interpreting the findings of this study. First, the sample consisted of 45 students enrolled in three construction engineering courses at a single institution. Although the courses represent multiple levels within the undergraduate curriculum, the sample size and institutional context limit the generalizability of the findings. Future research involving multi-institutional deployment would strengthen external validity.

Second, the study employed an exploratory instructional design rather than a controlled experimental framework. While the within-subject comparison of collaboration modes reduces scenario variability, the absence of randomized group assignment and inferential statistical testing limits causal interpretation. The results should therefore be understood as indicative patterns that inform instructional design rather than definitive claims of effectiveness.

Third, performance measures were based on structured task responses and descriptive comparison across modes. Although accuracy differences were observed, deeper measures of long-term learning retention, transferability, and metacognitive development were not assessed in this initial deployment. Future iterations may incorporate longitudinal tracking or validated learning assessment instruments.

Finally, student reflections were analyzed thematically to identify recurring perceptions related to trust, autonomy, and cognitive support. While this qualitative analysis provides valuable insight into student experience, it does not constitute a fully coded qualitative study with formal inter-rater reliability metrics. Subsequent studies may adopt mixed methods designs to enhance analytical rigor.

9. conclusion and future work

This study introduced a scenario-based instructional platform built on n8n workflows and LLM-powered assistants to support learning activities in construction and civil engineering courses. By implementing and comparing three AI–human collaboration modes, the study demonstrated the pedagogical value of allowing students to experience and evaluate different forms of AI-supported decision-making within realistic infrastructure inspection scenarios.

The results indicate that although AI-guided modes can improve efficiency, students tended to prefer AI-assisted modes where they retained primary control over decision making. This balance between human judgment and AI support appears to promote deeper cognitive engagement and reflective learning. The reflection responses also revealed how students interpreted issues such as trust in AI recommendations, their sense of autonomy, and their responsibility in final decision making.

Future development of the platform will focus on several areas. First, scalability will be evaluated through deployment in larger classes and across multiple course levels. Second, the framework will be adapted for other engineering domains beyond construction, enabling broader use in engineering education. Third, future studies will incorporate more formal learning outcome assessments to evaluate how AI-supported scenario-based learning influences student reasoning, decision confidence, and critical thinking.

As AI tools become more common in engineering practice, educators must consider how students develop judgment, responsibility, and critical thinking when working with AI-supported systems. The framework described in this paper provides one possible model for integrating AI-supported learning activities into engineering curricula.

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